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Intelligent Distribution of Fresh Agricultural Products in Smart City

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***Abstract*—With the construction of smart cities and the continuous improvement of people's living standards, residents' demand for fresh agricultural products (FAP) has increased dramatically. Therefore, reasonable arrangement for intelligent distribution of FAP in smart cities can effectively guarantee product quality, improve distribution efficiency, reduce distribution cost, and increase customer satisfaction. In actual distribution in smart city, road conditions are one of the important factors that affect the distribution. Therefore, according to the influence of road conditions on refrigerated vehicle's (RV's) speed, the RV's speed characteristic models are established. Meanwhile, according to the characteristics of FAP, the penalty cost function based on the time window is constructed. According to the idea of fuzzy logic, the customer satisfaction evaluation model is established. Then, in order to minimize the distribution costs and maximize customer satisfaction as the optimization goal of intelligent distribution in smart city, the mathematical model is built. For solving this model, an improved quantum-behaved particle swarm optimization algorithm (IQPSO) is proposed. Finally, the effectiveness of IQPSO is verified by simulation. The results show that IQPSO also achieves good results, and the model constructed can effectively balance the relationship between the distribution costs and customer satisfaction when distributing FAP in smart city.**

***Index Terms*—Fresh agricultural products, intelligent distribution, vehicle routing, customer satisfaction, smart city**

I. Introduction

With the continuous development of urbanization and smart cities, more and more FAP are delivered to customers through Online to Offline (O2O) mode. The consumption of fresh agricultural products (FAP) between urban and rural residents increases year by year. Meanwhile, residents put forward higher requirements for timeliness and FAP's quality in distribution process. Therefore, how to arrange the distribution route scientifically and rationally to ensure the freshness of FAP, improve the distribution efficiency, trade off the distribution cost and customer satisfaction is one of the important problems for distribution in smart city.

The substance of smart city is to make use of advanced information technology to realize urban smart management and operation, to create a better life for people in the city. However, efficient logistics is one of the essential links to improve service level of smart city. Therefore, it is necessary to study intelligent distribution in smart cities. The vehicle routing problem (VRP) firstly proposed in 1959 is a classical problem in logistics and transportation. Since then, many research results have been produced on this optimization problem. Pan et al. [1] established a distribution vehicle path optimization model for urban transportation based on time-dependent travel time, multiple trips per vehicle, and loading time at the depot simultaneously. Based on service time window constraints, Wang et al. [2] considered the penalty cost, obtaining the VRP model with soft time windows. Brandsttter [3] solved the distribution path optimization problem with time window through a metaheuristic algorithm. However, most of literatures only assume that distribution cost is related to distribution distance, and rarely considers the relationship between cost and vehicle speed, as well as the impact of road conditions on cost.

Aiming at the optimization model of cold chain logistics distribution path under time-varying conditions, Woensel et al. [4] considered the dynamic driving speed and proposed an improved Tabu Search algorithm to find the balance point between delivery service quality and distribution cost. Zhang et al. [5] proposed a hybrid solution algorithm combining Tabu search and Artificial Bee Colony algorithm. Ma et al. [6] studied the VRP with road constraint based on Tabu Search algorithm. As for customer satisfaction evaluation in logistics distribution, Qin et al. [7] used the punctuality of distribution as evaluation standard. In order to evaluate customer satisfaction, Ghannadpour et al. [8] used a function of fuzzy time windows when studying multi-objective dynamic VRP. Bakeshloo et al. [9] also adopted function of fuzzy time windows to evaluate customer satisfaction. However, the above literatures mainly consider a single factor affecting the distribution cost (i.e., vehicle speed, road conditions), rarely analyze the impact of weather conditions and different distribution times on the speed of distribution vehicles and distribution cost. In addition, most of literatures above only evaluates customer satisfaction based on distribution punctuality. However, the customer satisfaction evaluation of FAP should not only consider the timeliness of distribution, but also quality of products in the process of distribution. In the view of the above analysis, we analyze the following problems: 1) Under different weather conditions and time periods, how does the time-varying speed of RV affect the

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distribution costs? 2) Considering the main factors that affect the evaluation of customer satisfaction, how can we get an accurate evaluation value of customer satisfaction, thereby guiding the intelligent distribution in smart cities? 3) In the FAP's distribution in smart cities, how do we rationally and scientifically formulate a distribution plan for FAP that considers both distribution cost and customer satisfaction?

Therefore, according to temporal and spatial characteristics of RV's speed, we establish the speed model. Then, according to the nature of on-time delivery and the product quality in the FAP's distribution, we proposed a novel customer satisfaction based on fuzzy logic. Finally, the multi-objective optimization problem is constructed, which is solved by an improved quantum-behaved particle swarm optimization algorithm (IQPSO). The main contributions of our work are as follows:

1) Based on the description of the space-time characteristics of the distribution vehicle speed, the influence rates of the distribution vehicle speed, which is under different weather conditions and different time periods, are established.

2) The evaluation of customer satisfaction is generally a subjective description, not an accurate value. Therefore, by adopting the method of fuzzy logic, the accurate value of customer satisfaction evaluation is obtained.

3) An improved quantum-behaved particle swarm optimization algorithm is proposed, which can effectively solve the multi-objective optimization problem that are minimizing distribution costs and maximizing customer satisfaction.

The remainder of this paper is organized as follows. In the next section, the system model will be described in detail. In Section 3, the composition of distribution costs will be analyzed one by one. In Section 4, another optimization index, customer satisfaction, will be analyzed. In Section 5, a formal mathematical description of the problem is given and we describe the algorithm proposed in detail. Thereafter, in Section 6, the simulation and experiment are carried out. Finally, some conclusions are drawn in Section 7.

II. System Model

A. Principle of FAP Intelligent Distribution System

In the intelligent distribution system of FAP in smart cities, each customer periodically transmits the order information to the data center located at fresh agricultural products distribution center (FAPDC). Then, the FAPDC arranges RV for distribution tasks based on the received orders and the traffic and weather conditions prediction information. At the same time, FAPDC feeds back the arrival time to customers. The schematic diagram of the system is shown in Fig. 1.

B. Assumptions of FAP Intelligent Distribution

The essence of the described intelligent distribution in smart city is to make reasonable plans for the route of distribution vehicle. That is the closed vehicle routing problem with single supply point and multiple demand points. Specifically, there are several RVs for scheduling in FAPDC. RVs are arranged for distribution based on customers' demand. Starting from FAPDC, RVs send FAP to customers according to the planned

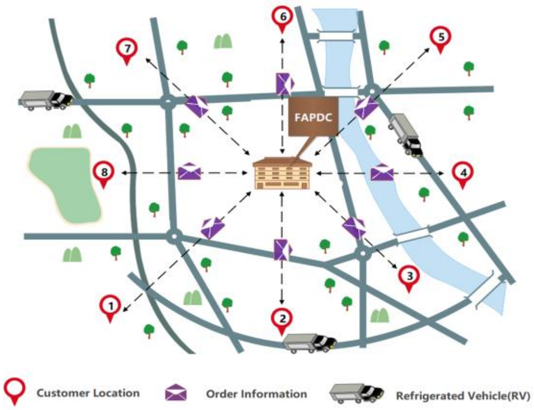

Fig. 1. Schematic Diagram of Intelligent Distribution of Fresh Agricultural Products in Smart City

routes, and finally return to FAPDC. Therefore, how to arrange distribution routes is still a challenge for FAP's intelligent distribution in smart cities. To facilitate analysis of the problem, some assumptions are illustrated as follows:

(1) Each customer is only visited once by RV.

(2) The total product demand on each planned route cannot exceed the rated load of the RV.

(3) When the RV arrives within the time windows requested by customer, customer will be completely satisfied for logistics service. Otherwise, it will reduce customer satisfaction and produce penalty cost.

The described problem has two optimization objectives, i.e., 1) to minimize the distribution costs and 2) to maximize the customer satisfaction. Therefore, the following multi-objective optimization model is constructed as:

$$\begin{cases} Min & \text{distribution costs} \\ Max & \text{customer satisfaction} \end{cases} \quad (1)$$

where distribution costs include the RV transportation cost, the damage cost of FAP and the time window penalty cost. Customer satisfaction refers to the satisfaction degree of the served customer, which is related to the RV arrival time and the quality of FAP.

C. Symbols

Based on the needs of building the model, this paper uses the corresponding symbols which are listed in TABLE I.

TABLE I
Description of The Symbols

Symbols	Description
$\check{C}$	The distribution costs of distribution process;
C_1	The cost of the RV transportation;
C_2	The damage cost of FAP;
C_3	The penalty cost;
C_{11}	The operation cost of RVs;
C_{22}	The running cost of RVs;
N	The number of arranged RVs $(n = 1,2,3, \dots \dots, N)$;
$\tilde{c}$	The operation cost of one RV;
$\hat{c}$	The running cost of per unit time;
t_{ij}	The time of RV from customer i to customer j;
d_{ij}	The distance between customer i and customer j;
$\hat{s}_v$	The driving speed of RV;

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$\bar{s}_v$	The average driving speed of RV;
ζ_{con}	The influence rate of RV's speed;
ζ_{Sun}	The influence rate of RV's speed while sunny;
ζ_{Rain}	The influence rate of RV's speed while rainy;
ζ_{Snow}	The influence rate of RV's speed while snowy;
ζ_{Fog}	The influence rate of RV's speed while foggy;
$\hat{q}_i$	The demand of customer i;
$\hat{p}$	The unit price of FAP;
φ	The time sensitivity of FAP's quality;
t_i	The arrival time of RV to customer i;
C_3^i	The penalty cost when RV arrives at customer i;
M	A larger positive number;
α_c	Depending on customer's requirement for distribution time ($\alpha_c < 0$);
β_c	Depending on customer's requirement for distribution time ($\beta_c < 0$);
$[0, \tilde{t}_i^l)$	The time window that customer i refuses to receive products;
$(\tilde{t}_i^h, +\infty)$	The time window that customer i refuses to receive products;
$[t_i^l, t_i^h]$	The ideal time window expected by customer i;
$[\tilde{t}_i^l, t_i^l)$	When the RV arrives in $[\tilde{t}_i^l, t_i^l)$, FAPDC will pay some penalty costs;
$(t_i^h, \tilde{t}_i^h]$	When RV arrives in $(t_i^h, \tilde{t}_i^h]$, which will have a greater impact on product quality and sale period, the penalty cost will be paid;
c_i	The damage cost when FAP is delivered to customer i;
ξ_i^Q	The quality satisfaction of customer i;
ξ_i^T	The time satisfaction of customer i;;
ξ^Q	The quality satisfaction;
ξ^T	The time satisfaction;
t_i^s	The service time of RV k at customer i;
v_n	0-1 variable, $v_n = 1$ if the RV n carries out the distribution task, otherwise $v_n = 0$;
x_{ijn}	0-1 variable, $x_{ijn} = 1$ if the RV n visits customer j from customer i, otherwise $x_{ijn} = 0$;
y_{in}	0-1 variable, $y_{in} = 1$ if customer i is visited by RV n; otherwise $y_{in} = 0$.

III. Analysis of Distribution Costs

The distribution costs are the total fees paid in the distribution process. It consists of the RV transportation cost C_1, the damage cost of FAP C_2 and the penalty cost C_3. Therefore, distribution costs Č can be expressed as:

$$\check{C} = C_1 + C_2 + C_3 \tag{2}$$

A. RV Transportation Cost Analysis

The RV transportation cost is the total cost of RVs to complete a certain amount of transportation, which consists of operation cost of RVs C_{11} and running cost of RVs C_{22}. RV transportation cost C_1 can be expressed as:

$$C_1 = C_{11} + C_{22} \tag{3}$$

The operation cost of RVs refers to total expenditure of the logistics enterprise in a certain period of operation activities, that is, drivers' salaries, wear and tear of RVs, etc. Thus, the operation cost of RVs C_{11} can be expressed as:

$$C_{11} = \sum_{n=1}^{N} \tilde{c} \times v_n \tag{4}$$

where N is the number of arranged RVs for distribution, ($n = 1,2,3,\ldots\ldots,N$).

The running cost of RVs C_{22} are expressed as:

$$C_{22} = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{n=1}^{N} \hat{c} \times t_{ij} \times x_{ijn} \tag{5}$$

where i and j ($i, j = 0,1,2,\ldots\ldots,N$) represent customers, 0 represents the FAPDC. t_{ij} is the running time of RV, which can be expressed as:

$$t_{ij} = d_{ij}/\hat{s}_v \tag{6}$$

where $\hat{s}_v$ is RV's speed, which can be expressed as:

$$\hat{s}_v = \bar{s}_v(1 - \zeta_{con}) \tag{7}$$

where $\bar{s}_v$ is the average driving speed of RV; It is noted that $\zeta_{con}(con = Sun, Rain, Snow, Fog)$ is the main factor to establish RV's speed feature model, which is named as the influence rate of RV's speed.

In order to accurately describe the space-time characteristics of RV speed, through China Automobile Technology Research Center—Actual Monitoring Data of China Automobile Working Condition Information System Platform, we get these data that include the effects of different weather conditions, road conditions, and time periods on RV speed. Through data processing and analysis, we establish the influence rate of RV speed model under different weather conditions and time periods. And the influence rate of RV speed $\zeta_{con}(con = Sun, Rain, Snow, Fog)$ is expressed as:

$$\zeta_{Sun} = \begin{cases} 0, & 0 \le t < 6 \text{ or } 22 \le t < 24 \\ 0.225 \times t - 1.35, & 6 \le t < 8 \\ -0.05 \times t + 0.85, & 8 \le t < 12 \\ t/30 - 0.15, & 12 \le t < 18 \\ -0.1125 \times t + 2.475, & 18 \le t < 22 \end{cases} \tag{8}$$

$$\zeta_{Rain} = \begin{cases} 0.2, & 0 \le t < 6 \text{ or } 22 \le t < 24 \\ 0.2 \times t - 1, & 6 \le t < 8 \\ -0.05 \times t + 1, & 8 \le t < 12 \\ t/30, & 12 \le t < 18 \\ -0.1 \times t + 2.4, & 18 \le t < 22 \end{cases} \tag{9}$$

$$\zeta_{Snow} = \begin{cases} 0.5, & 0 \le t < 6 \text{ or } 22 \le t < 24 \\ 0.1 \times t - 0.1, & 6 \le t < 8 \\ -0.05 \times t + 0.85, & 8 \le t < 12 \\ t/30 + 0.1, & 12 \le t < 18 \\ -0.05 \times t + 1.6, & 18 \le t < 22 \end{cases} \tag{10}$$

$$\zeta_{Fog} = \begin{cases} 0.5, & 0 \le t < 6 \text{ or } 22 \le t < 24 \\ 0.05 \times t + 0.2, & 6 \le t < 8 \\ -0.075 \times t + 1.2, & 8 \le t < 12 \\ 0.025 \times t, & 12 \le t < 18 \\ -0.0125 \times t + 0.225, & 18 \le t < 22 \end{cases} \tag{11}$$

According to the above analysis, Eq. (3) can be rewritten as:

$$C_1 = \sum_{n=1}^{N} \tilde{c} \cdot v_n + \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{n=1}^{N} \hat{c} \cdot t_{ij} \cdot x_{ijk} \tag{12}$$

B. Damage Cost of FAP Analysis

The FAP's quality is mainly affected by temperature and time of distribution. Considering that FAP are distributed by RV, the temperature of distribution process is relatively stable. The time of distribution process is considered as the main influence on damage cost. Therefore, the FAP's damage cost C_2 can be expressed as follow:

$$C_2 = \sum_{i=0}^{N} \hat{q}_i \times \hat{p} \times \left(\frac{2}{\pi} \times \arctan(\varphi \times t_i)\right) \quad (13)$$

C. Penalty Cost Analysis

Different from the hard time window, the VRP with soft time window requires RV to arrive within the time window as soon as possible, otherwise a certain penalty will be given [10]. Thus, the soft time window is adopted. The penalty cost based on the soft time window C_3 can be expressed as:

$$C_3 = \sum_{i=1}^{N} C_3^i(t_i) \quad (14)$$

where $C_3^i(t_i)$ means one penalty cost when RV arrives at customer i, which is expressed as:

$$C_3^i(t_i) = \begin{cases} M\,, & 0 \le t_i < \tilde{t}_i^l \text{ or } t_i > \tilde{t}_i^h \\ \alpha_c \times (t_i - t_i^l)\,, & \tilde{t}_i^l \le t_i < t_i^l \\ \exp[-\beta_c \times (t_i - t_i^h)] - 1, & t_i^h < t_i \le \tilde{t}_i^h \\ 0\,, & t_i^l \le t_i \le t_i^h \end{cases} \quad (15)$$

where RV arrives in $[0, \tilde{t}_i^l)$ or $(\tilde{t}_i^h, +\infty)$, customer i refuses to receive products and FAPDC will suffer a huge penalty cost. When RV arrives at the ideal time window expected by customer i, that is, RV arrives at $[t_i^l, t_i^h]$, the penalty cost needs not to be paid. When the RV arrives in $[\tilde{t}_i^l, t_i^l)$, FAPDC will pay some penalty costs and the penalty cost varies linearly with time. However, when RV arrives in $(t_i^h, \tilde{t}_i^h]$, which will have a greater impact on product quality and sale period, the penalty cost that FAPDC will bear changes exponentially, as shown in Fig. 2.

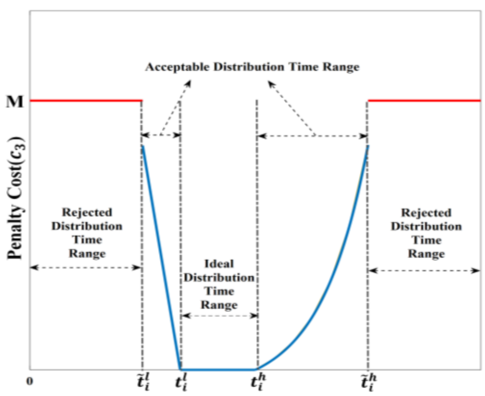

Fig. 2. Schematic diagram of time-window penalty cost.

IV. Customer Satisfaction Based on Fuzzy Logic

In the distribution process, customer satisfaction is mainly affected by the FAP's quality and the RV's arrival time. Obviously, evaluation of customer satisfaction is a multi-factor decision making process [11]. The multi-factor decision making processes are mainly relying on precise value of judgment parameters [12], which are always featured with fuzziness in real life. For instance, "the FAP's quality is good". Obviously, these expressions are highly subjective, and cannot be expressed with exact values. However, fuzzy logic is a mathematical method to exactly cope with the imprecise and incomplete information problem [13]. Therefore, we put forward an effective evaluation method to solve the fuzzy and uncertain problem for customer satisfaction evaluation. The customer satisfaction evaluation based on fuzzy logic consists of 3 stages: fuzzification, fuzzy inference and defuzzification.

A. Judgment Parameters Fuzzification

In this paper, the FAP's quality and the RV's arrival time are adopted as judgement parameters.

The FAP's quality is reflected by its damage cost. The lower the damage cost is, the less the loss is, and the higher the quality is. Thus, Based on Eq. (13), the FAP's damage cost when RV arriving at customer i is:

$$c_i = \hat{q}_i \times \hat{p} \times \left(\frac{2}{\pi} \times \arctan(\varphi \times t_i)\right) \quad (16)$$

Quality satisfaction is defined as one judgement parameter, which means the satisfaction degree of customer for the FAP's quality. It is expressed as

$$\xi_i^Q = \exp(-\eta_i) \quad (17)$$

where η_i is the normalized the rate of FAP's damage cost, and $\eta_i = c_i / C_2$.

Time satisfaction is adopted as another judgement parameter. Specially, when the RV arrives at customer i in $[\tilde{t}_i^l, t_i^l)$ or $(t_i^h, \tilde{t}_i^h]$, customer i will not be satisfied. However, customer i will be satisfied if RV reaches there in $[t_i^l, t_i^h]$. Based on the questionnaire results of distribution time intention, the time satisfaction of customer i, ξ_i^T, is constructed as follow:

$$\xi_i^T(t_i) = \begin{cases} 0\,, & 0 \le t_i < \tilde{t}_i^l \text{ or } t_i > \tilde{t}_i^h \\ 1 - \alpha_\varsigma \times (t_i^l - t_i)\,, & \tilde{t}_i^l \le t_i < t_i^l \\ 1 - e^{-[\beta_\varsigma \times (\tilde{t}_i^h - t_i)]}\,, & t_i^h \le t_i < \tilde{t}_i^h \\ 1\,, & t_i^l \le t_i < t_i^h \end{cases} \quad (18)$$

where α_ς and β_ς are constants greater than zero.

Based on the above analysis, the quality satisfaction ξ^Q and the time satisfaction ξ^T are adopted as the input linguistic variables. To achieve a good balance between the accuracy of analysis and the amount of calculation, the input linguistic variable based on the quality satisfaction is divided into three fuzzy sets: excellent (E), good (G), poor (P). The input linguistic variable based on the time satisfaction is divided into five fuzzy sets: too early (TE), early (E), punctual (P), late (L), too late (TL). They are expressed as below:

$$\begin{cases} \overline{T}(\xi^Q) = \overline{T}\{E, G, P\} \\ \overline{T}(\xi^T) = \overline{T}\{TE, E, P, L, TL\} \end{cases} \quad (19)$$

Moreover, the judgment result is divided into five linguistic terms: great satisfaction (GS), the more satisfied (TMS), common (C), not very satisfied (NVS), very dissatisfied (VD). Then, the fuzzy set of output variable $j^{Q/T}$ is expressed as:

$$\overline{T}(j^{Q/T}) = \overline{T}\{GS, TMS, C, NVS, VD\} \quad (20)$$

The fuzzification process is the process of solving different judgment parameters to belong to the membership of different fuzzy sets through the membership function. The membership function is the building blocks of fuzzy set theory, i.e., fuzziness in a fuzzy set is determined by its membership function. Accordingly, the shape of membership function is important for a particular problem since they have a profound effect on fuzzy inference system [14]. Gaussian membership function has been successfully utilized in past work [15]. Thus, the Gaussian function is selected as the membership function of various fuzzy set.

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$$f_{r,m}(B_r) = \exp\left[-\left(B_r - \delta_{r,m}\right)^2 / \left(\sigma_{r,m}\right)^2\right] \quad (21)$$

where $B_r(r = 1,2,3)$ are respectively the input variables ξ^Q, ξ^T, and the output variable $j^{Q/T}$; m is the m-th fuzzy set of the B_r; $\delta_{r,m}$ and $\left(\sigma_{r,m}\right)^2$ are the corresponding mean value and variance of the Gaussian membership function respectively.

B. Fuzzy Inference Rules Establishment

Based on the actual experience, fuzzy inference rule is established for guaranteeing the FAP's quality and ensuring the accuracy of distribution time, as shown in TABLE II. In our study, the inference is based on the Mamdani's method.

TABLE II
FUZZY INFERENCES RULES

Time Satisfaction	Quality Satisfaction	Fuzzy Inference Rules
Too early (TE)	Excellent (E)	Not very satisfied (NVS)
	Good (G)	Not very satisfied (NVS)
	Poor (P)	Very dissatisfied (VD)
Early (E)	Excellent (E)	The more satisfied (TMS)
	Good (G)	Common (C)
	Poor (P)	Very dissatisfied (VD)
Punctual (P)	Excellent (E)	Great satisfaction (GS)
	Good (G)	Great satisfaction (GS)
	Poor (P)	Common (C)
Late (L)	Excellent (E)	The more satisfied (TMS)
	Good (G)	Common (C)
	Poor (P)	Very dissatisfied (VD)
Too late (TL)	Excellent (E)	Not very satisfied (NVS)
	Good (G)	Not very satisfied (NVS)
	Poor (P)	Very dissatisfied (VD)

C. Defuzzification

In fuzzy logic, defuzzification is a process transforming the fuzzy output value into the exact judgment value. In this paper, the method of centriod [16] is employed to defuzzify the judgment result. In this paper, h_i is denoted as the judgment (output) value of customer i, which is obtained by fuzzy logic.

V. MODEL ESTABLISHMENT AND ALGORITHM DESIGN

A. Model Establishment

According to the above analysis, the FAP's intelligent distribution in smart cities is established as a model of multi-objective optimization:

$$\min \check{C} = \sum_{n=1}^{N} \tilde{c} \times v_n + \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{n=1}^{N} \hat{c} \times t_{ij} \times x_{ijn} + \sum_{i=0}^{N} \hat{q}_i \times \hat{p} \times \left(\frac{2}{\pi} \times \arctan(\varphi \times t_i)\right) + \sum_{i=0}^{N} C_3^i(t_i) \quad (22)$$

$$\max S = \sum_{i=1}^{N} h_i \quad (23)$$

$$s.t.\ \ t_j = \sum_{i=0}^{N}\sum_{n=1}^{N} x_{ijn} \times \left(t_i + t_{ij} + t_i^s\right), \quad t_0 = 0, t_0^s = 0, j = 1,2,\ldots\ldots,N \quad (24)$$

$$\sum_{j=0}^{N} x_{0jn} = \sum_{j=0}^{N} x_{j0n} \le 1, n = 1,2,\ldots\ldots,N \quad (25)$$

$$\sum_{i=0}^{N} x_{ipn} - \sum_{j=0}^{N} x_{pjn} = 0, \quad n = 1,2,\ldots\ldots,N; p = 1,2,\ldots\ldots,N \quad (26)$$

$$\sum_{i=0}^{N}\sum_{n=1}^{N} x_{ijn} = 1, j = 1,2,\ldots\ldots,N \quad (27)$$

$$\sum_{j=0}^{N}\sum_{n=1}^{N} x_{ijn} = 1, i = 1,2,\ldots\ldots,N \quad (28)$$

$$\sum_{i=1}^{N} \hat{q}_i \times y_{in} \le Q, n = 1,2,\ldots\ldots,N \quad (29)$$

where constraint (22) and constraint (23) indicate that the objective functions are to minimize distribution costs and to maximize customer satisfaction. constraint (24) represents the time when the RV arrives at customer i, and t_i^s means time that RV remains at customer i. Constraints (25), (26) show that all RVs must start from the FAPDC and return to the FAPDC when their distribution tasks are achieved. constraint (27) and constraint (28) represent that each customer is only visited once by one vehicle. constraint (29) ensures that the total load on each RV cannot exceed the rated load. The above optimization problem is a VRP with time windows (VRPTW), which has been proved to be a NP hard problem [17].

B. Algorithm Design

VRPTW problem is usually solved by heuristic algorithm [18]. Particle swarm optimization (PSO) has an ideal optimization effect in solving VRPTW problem. However, in the practical application, which cannot converge to the global optimal solution with probability 1 [19]. Thus, in combination with the quantum-behaved particle swarm optimization in previous literature [20], an improved quantum-behaved particle swarm optimization algorithm (IQPSO) was proposed in this paper to solve the VPRTW problem. The main components of IQPSO are as follow.

1) IQPSO Algorithm

In quantum space, the quantum state of a particle is described by the wave function $\Psi(X,t)$, instead of the positon X and velocity V of particles depicted in PSO. The probability density of a particle's appearance in a certain position can be obtained from $|\Psi(X,t)|^2$, then, we can get the probability distribution function. And the particle's position can be updated according to Eq. (30) through the Monte Carlo stochastic simulation method [21].

$$X_{\tilde{\imath},\tilde{\jmath}} = p_{\tilde{\imath},\tilde{\jmath}} \pm (L/2) \times \ln(1/u), u \sim \mathrm{U}(0,1) \quad (30)$$

where $p_{\tilde{\imath},\tilde{\jmath}}$ is a local attractor that can be defined as:

$$p_{\tilde{\imath},\tilde{\jmath}} = \varphi_{\tilde{\imath},\tilde{\jmath}} \times pbest_{\tilde{\imath},\tilde{\jmath}} + \left(1 - \varphi_{\tilde{\imath},\tilde{\jmath}}\right) \times gbest_{\tilde{\jmath}} \quad (31)$$

where $\tilde{\imath}$ represents the $\tilde{\imath}$-th particle, $\tilde{\imath} = 1,2,\ldots\ldots,M$. d is the dimension of the search space. $\tilde{\jmath} = 1,2,\ldots\ldots,d$. $pbest$ is the best position for particles. $gbest$ is the optimal position of the whole particles. $\varphi_{\tilde{\imath},\tilde{\jmath}}$ is a uniformly distributed random number on the interval $(0,1)$, that is, $\varphi_{\tilde{\imath},\tilde{\jmath}} \sim \mathrm{U}(0,1)$.

However, quantum-behaved particle swarm optimization cannot avoid falling into the local optimum position when used to optimize the multimodal functions, therefore, for IQPSO algorithm, Eq. (31) is modified as:

$$p_{\tilde{\imath},\tilde{\jmath}} = \vartheta^1 \times \acute{\beta} \times pbest_{\tilde{\imath},\tilde{\jmath}} + \vartheta^2 \times \left(1 - \acute{\beta}\right) \times gbest_{\tilde{\jmath}}, \acute{\beta} \sim \mathrm{U}(0,1) \quad (32)$$

where ϑ^1 and ϑ^2 are weighted coefficients, which can be expressed as follows:

$$\vartheta^1 = [\mu \times (L_c - C_c)]/C_c \quad (33)$$

$$\vartheta^2 = (\mu \times C_c)/L_c \quad (34)$$

where μ is a positive constant. C_c and L_c are the current number of iterations and the total number of iterations of IQPSO.

L can be evaluated by:

$$L = 2\alpha\left|mbest - X_{\tilde{\imath},\tilde{\jmath}}\right| \quad (35)$$

where α is known as the search expansion coefficient. In the paper, $\alpha = 0.5 + 0.5 \times [(L_c - C_c)/L_c]$. $mbest$ is the mean value of the optimal position found for each particle so far, that is, the average optimal position [22]. It can be expressed as:

$$mbest = \frac{1}{M} \times (\sum_{\tilde{\imath}=1}^{M} pbest_{\tilde{\imath}}) \quad (36)$$

Therefore, Eq. (30) can be modified as:

$$X_{\tilde{\imath},\tilde{\jmath}} = p_{\tilde{\imath},\tilde{\jmath}} \pm \alpha \left| mbest - X_{\tilde{\imath},\tilde{\jmath}} \right| \times \ln(1/u), u \sim \mathrm{U}(0,1) \quad (37)$$

The pseudo-code for IQPSO algorithm to perform the steps is given below.

2) Complexity Analysis

Computational complexity is used to describe an algorithm's use of computational resources. For the IQPSO, we do not consider the computational cost of the average best position of particles, the local attractor, the location of each particle and the fitness of each particle because they are constant for each updating step. The computational complexity is related to the complexity incurred in each iteration and the complexity of updating generations. Therefore, the computational complexity is $O(M \times L_c)$, where M is the number of population size and L_c is the maximum number of iterations.

Algorithm: Improved Quantum-behaved Particle Swarm Optimization Algorithm

1: Input μ, maximum number of iterations L_c and population size M;
2: Initialize the location of each particle $X_{\tilde{\imath}}$ in the population according to Eq. (37);
3: Calculate the fitness of each particle: $F_{fitness} = w_1 \times \breve{C} + w_2 \times S$; w_1 and w_2 are the coefficient associated with fitness calculation;
4: Select the position of the particle corresponding to the minimum fitness of whole particles, and set $X_{\tilde{\imath}}^{min(F_{fitness})}(0) = pbest_{\tilde{\imath}}(0) = gbest(0)$;
5: **for all** $C_c = 1$ to L_c **do**
6: **for all** $\tilde{\imath} = 1$ to M **do**
7: Calculate the average best position of particles based on Eq. (36);
For each particle, calculate the local attractor $p_{\tilde{\imath}d}$ based on Eq. (32);
Calculate the location of each particle $X_{\tilde{\imath}}$ based on Eq. (37);
8: **end for**
9: Calculate the fitness of each particle $F_{fitness}$;
9: Calculate the fitness of each particle $F_{fitness}$;
10: Update the optimal position for each particle:
for all $\tilde{\imath} = 1$ to M **do**
if $F_{fitness}(X_{\tilde{\imath}}(C_c)) \geq F_{fitness}(pbest_{\tilde{\imath}}(C_c - 1))$ **then**
$pbest_{\tilde{\imath}}(C_c) = pbest_{\tilde{\imath}}(C_c - 1)$;
else
$pbest_{\tilde{\imath}}(C_c) = X_{\tilde{\imath}}(C_c)$;
end if
end for
11: Update the optimal position of the whole particles:
for all $\tilde{\imath} = 1$ to M **do**
if $F_{fitness}(pbest_{\tilde{\imath}}(C_c)) \geq F_{fitness}(gbest(C_c - 1))$ **then**
$pbest_{\tilde{\imath}}(C_c) = gbest(C_c - 1)$;
else
$pbest_{\tilde{\imath}}(C_c) = pbest_{\tilde{\imath}}(C_c)$;
end if
end for
12: **end for**
13: Return the minimum distribution cost and the maximum customer satisfaction.

VI. Simulation and Analysis

In this chapter, the effectiveness of IQPSO is, firstly, tested with standard test functions. After that, relevant analysis is made on the selection of parameters. Finally, taking a fresh cold chain logistics distribution company in a smart city as an example, a simulation experiment is performed and the results obtained by Genetic Algorithm (GA) and Ant Colony Algorithm (ACA) are analyzed. Simulation environment: Windows 10, Intel i7-8565U, 8GB RAM. Simulation platform: MATLAB R2016b.

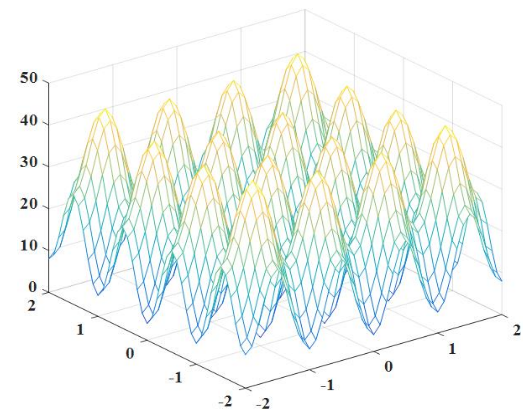
A. Standard Test Function Results and Analysis

In order to verify the global optimization ability of IQPSO, the standard test functions are used to test its convergence and global optimization ability. The information about test functions is shown in TABLE III.

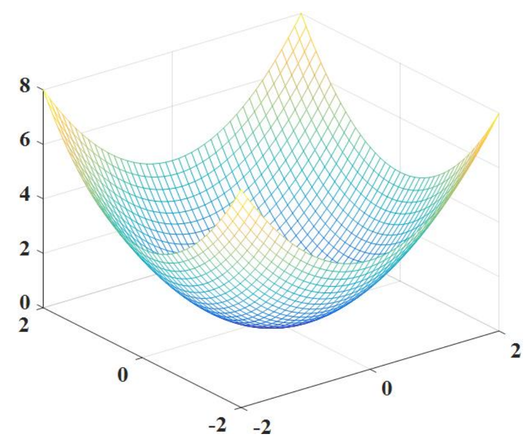
Generalized Rastrigin function uses cosine function to generate many local minimum values. It is often adopted by testing the global optimization ability of the optimization algorithm.

TABLE III
Standard Test Function

Function	Mathematical Expression	Optimal Solution
Generalized Rastrigin	$\sum_{\tilde{\imath}}^{\rho} [(x_{\tilde{\imath}})^2 - 10\cos(2\pi x_{\tilde{\imath}}) + 10]$	0
Sphere Model	$\sum_{\tilde{\imath}}^{\rho} (x_{\tilde{\imath}})^2$	0



(a) Generalized Rastrigin Function



(b) Sphere Model Function

Fig. 3. Standard Test Function

Sphere Model function is a nonlinear symmetric unimodal function. It is mainly used to test the optimization accuracy of the algorithm.

The mathematical graph, containing Generalized Rastrigin function and Sphere Model function with two independent variables, is shown in Fig. 3.

TABLE IV and TABLE V show the test results for test functions respectively. The population size is set as 20， 40 and

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80, and the maximum number of iterations is set as 1000, 2000 and 3000, respectively. The dimension of the test function was set to 30.

The global optimization capability of each algorithm is tested by using the optimal value and the average optimization results respectively as two evaluation indexes. The value in parentheses is the average value of the test function found by each algorithm running 10 times. The value of the outside parentheses is the optimal value corresponding to the test found by each algorithm in 10 runs.

From the comparison of test results in TABLE IV and TABLE V, it shows that IQPSO has better performance in global convergence performance and accuracy. For Generalized Rastrigin function and Sphere Model function, IQPSO has obtained the global minimum value point in 10 runs, and each optimization is close to the global minimum value point.

TABLE IV
RESULTS OF GENERALIZED RASTRIGIN FUNCTION

Population Size	Number of Iteration	GA	ACA	IQPSO
20	1000	2.62e-08 (2.036)	3.81e-10 (3.14e-09)	0 (0.0041)
	2000	2.36e-08 (0.191)	2.93e-11 (8.26e-11)	0 (0.0034)
	3000	2.56e-09 (0.178)	9.92e-12 (3.52e-11)	0 (0.0017)
40	1000	1.37e-10 (0.082)	1.83e-10 (6.46e-10)	0 (0.0022)
	2000	1.61e-12 (0.061)	1.23e-11 (6.66e-11)	0 (0.0010)
	3000	1.17e-11 (0.063)	4.60e-12 (1.50e-11)	0(0.0007)
80	1000	4.30e-13 (0.133)	6.61e-11 (2.53e-10)	0 (0.0012)
	2000	1.63e-13 (0.086)	1.07e-11 (2.41e-11)	0 (0.0005)
	3000	9.83e-11 (0.096)	9.81e-13 (4.12e-12)	0 (0.0003)

According to the above analysis, IQPSO has an ideal performance in both convergence accuracy and global optimization capability. In addition, it can be seen from TABLE III and TABLE IV that when the population size becomes larger, the optimal value of fitness function becomes smaller and closer to the global optimal value. Therefore, when solving practical problems, the population size should be set to a larger number.

B. Simulation Parameters and Case Analysis

1) Simulation Parameters

According to field survey data, simulation parameters are set as follow. The fresh cold chain logistics distribution company owns several RVs with a load of 15 t, and provides cold chain distribution services for 17 customers. The location, demand and service time window of each customer are shown in TABLE VI. φ is 1/200; $\hat{p}$ is 10 yuan/kg; $\check{c}$ is 250 yuan/ one RV; $\hat{c}$ = 45 yuan/ h; α_c is -10; β_c is -0.05; $\bar{S}_v$ is 35 km/h.

2) Parameter Selection

In this paper, the fitness value based on the objective function is determined by the sum of distribution costs and customer satisfaction. In order to make distribution costs and

TABLE V
RESULTS OF SPHERE MODEL FUNCTION

Population Size	Number of Iteration	GA	ACA	IQPSO
20	1000	3.632e-13 (0.0136)	3.874e-3 (0.0344)	0 (3.655e-05)
	2000	1.232e-13 (0.0221)	1.965e-09 (1.034e-08)	0 (2.394e-05)
	3000	2.704e-12 (0.0146)	5.434e-4 (5.434e-3)	0 (1.567e-05)
40	1000	7.075e-15 (0.003)	4.124e-09 (1.274e-08)	0 (2.019e-05)
	2000	4.455e-16 (0.002)	5.683e-10 (1.711e-09)	0 (9.381e-06)
	3000	7.438e-13 (0.005)	2.557e-4 (2.557e-3)	0 (6.217e-06)
80	1000	4.261e-13 (0.005)	1.381e-09 (3.369e-09)	0 (4.927e-06)
	2000	2.198e-16 (0.003)	2.983e-10 (1.017e-09)	0 (1.938e-06)
	3000	4.433e-15 (0.004)	7.0788e-11 (1.593e-10)	0 (1.591e-06)

TABLE VI
SIMULATION PARAMETERS

No.	Coordinate	Demand(t)	Time Window ($\tilde{t}_i^l, t_i^l, t_i^h, \tilde{t}_i^h$)
0	(18.7,15.3)	—	—
1	(16.5,8.45)	1.5	(7:00,8:30,15:45,19:30)
2	(20.1,10.1)	1.2	(8:00,10:30,12:40,14:50)
3	(19.4,13.4)	2.8	(5:00,7:50,9:50,10:50)
4	(25.3,14.2)	1.5	(9:00,10:30,17:50,19:30)
5	(22,10.1)	0.8	(6:30,8:30,12:50,14:30)
6	(25.5,17)	2.0	(10:00,11:00,17:00,20:00)
7	(15.8,15.1)	1.3	(17:00,19:00,23:30,24:00)
8	(16.6,12.4)	1.5	(15:30,18:30,21:00,22:00)
9	(14.1,18.1)	1.1	(2:30,4:30,18:20,20:00)
10	(17.5,17.4)	1.3	(3:30,5:00,13:30,15:30)
11	(23.5,13.5)	1.9	(3:00,6:00,19:00,20:30)
12	(19.4,18.1)	2.6	(8:30,10:00,14:45,16:00)
13	(22.1,12.5)	2.5	(15:00,17:00,21:45,24:00)
14	(11.2,11)	2.3	(11:00,19:00,22:00,23:30)
15	(14.3,9.8)	0.9	(12:30.18:45,20:30,24:00)
16	(24,19.9)	1.7	(8:30,9:30,15:30,18:50)
17	(12.2,14.5)	2.0	(10:00,19:00,20:00,23:30)

TABLE VII
THE VALUE OF FITNESS BASED ON WEIGHTS OF TWO INDEXES

Project	w_1	w_2	$\breve{P}_1(\%)$	$\breve{P}_2(\%)$	Fitness Value
1	1	1	99.97	0.03	2865.0998
2	1	10000	3.088	96.912	104436.3112
3	1	8000	3.999	96.001	77500.6754
4	1	6000	5.346	94.654	62290.1190
5	1	4000	7.555	92.445	41383.0156
6	1	2000	14.258	85.742	22138.7204
7	1	1000	25.511	74.489	12448.3728
8	1	800	28.928	71.072	10762.8318
9	1	600	34.774	65.226	8866.0410
10	1	400	61.939	36.061	7206.6413
11	1	200	44.311	55.689	4505.0426
12	1	100	74.434	25.566	3861.2293
13	1	50	85.354	14.646	3423.7562

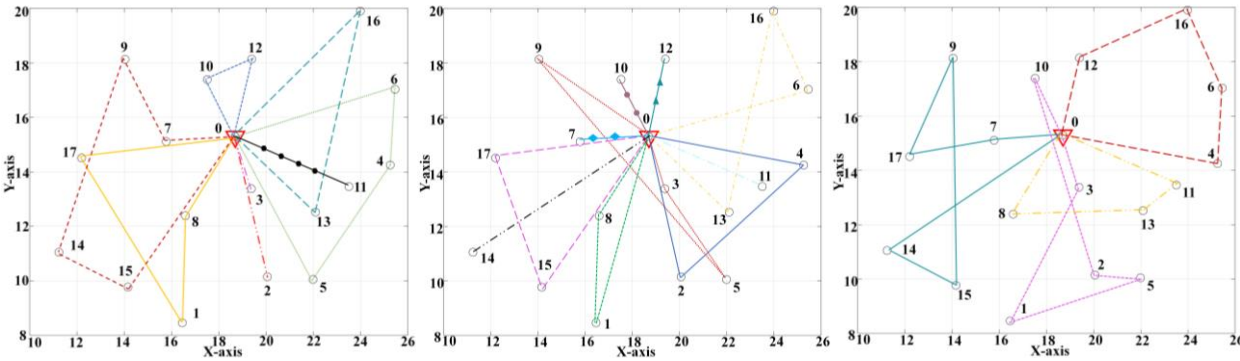
customer satisfaction have the same effect on the search performance of IQPSO, we adjust parameters w_1 and w_2 which are the weights of distribution costs and customer satisfaction. The population size is 20. The number of iterations is 2000. $\check{P}_1$ represents the proportion of distribution costs in fitness value. $\check{P}_2$ represents the proportion of customer satisfaction in fitness value. The experimental results are shown in TABLE VII.

According to the experimental results in TABLE VII, in order to balance the impact of distribution costs and customer satisfaction on fitness value, that is, both have the same determining effect on the search performance of IQPSO, we will select the weights of Project 11 for the next experiment. Because $\check{P}_1$ and $\check{P}_2$ in Project 11 account for 50% of the fitness value approximately. And the next experiment is to increase the population size when the number of iterations remains the same. The number of iterations in each project is 2000. The results of experiment are shown in TABLE VIII.

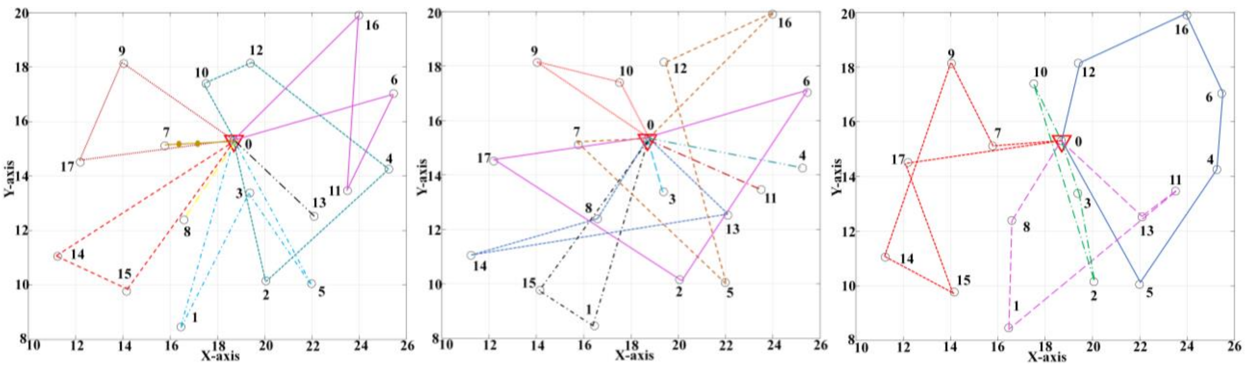
TABLE VIII
THE VALUE OF FITNESS BASED ON DIFFERENT POPULATION SIZES

Project	Population Size	w_1	w_2	Fitness Value
1	20	1	200	4770.2839
2	40	1	200	4761.0611
3	60	1	200	4599.7298
4	80	1	200	4444.1914
5	100	1	200	4494.7985
6	120	1	200	4762.001

As is shown in TABLE VIII, when the population size is 80, the fitness value in Project 4 is the minimum compared with other fitness values. In terms of fitness value, it, first, presents a decreasing trend. Secondly, when the population size increases to 100 and 120, the fitness value shows an increasing trend. Considering the fitness value of IQPSO, we will carry out the simulation experiment below with the population size of 80. And the number of iterations is 2000. And the weight of distribution costs is set to 1 and the weight of customer satisfaction is set to 200.



(a) Routes of IQPSO (b) Routes of GA (c) Routes of ACA
Fig. 4. Optimal Distribution Route for Different Algorithms in Sunshine.



(a) Routes of IQPSO (b) Routes of GA (c) Routes of ACA
Fig. 5. Optimal Distribution Route for Different Algorithms in Snow.

3) Case Analysis

Fig. 4 depicts the optimal distribution route of different algorithms in sunny days and the distribution route shown in this figure is the best route in 10 operations for each algorithm. Each distribution loop is taken by one RV.

The optimal number of RVs obtained by IQPSO is 8, GA is 10 and ACA is 4. The optimal distribution route of IQPSO is: 0-3-0; 0-2-0; 0-8-1-17-0; 0-6-4-5-0; 0-11-0; 0-12-10-0; 0-7-9-14-15-0; 0-13-16-0. The optimal distribution route of GA is: 0-11-0; 0-4-2-0; 0-3-5-9-0; 0-8-1-0; 0-13-16-6-0; 0-17-15-0; 0-12-0; 0-14-0; 0-10-0; 0-7-0. The optimal distribution route of ACA is: 0-14-15-9-17-7-0; 0-3-1-5-2-10-0; 0-12-16-6-4-0; 0-8-13-11-0.

TABLE IX
SIMULATION RESULTS FOR DIFFERENT ALGORITHM IN SUNSHINE

Algorithms	Number of RV	Cost/yuan	Customer satisfaction	Driving distance/km
IQPSO	8	2772.4996	8.40931	129.1467
GA	11	3378.26945	9.1152	150.1193
ACA	4	1729.76141	7.52427	101.5928

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TABLE IX compares four results (the number of RVs, distribution costs, customer satisfaction and driving distance of RVs) under sunny conditions. The comparison result is the average result obtained by different algorithms under 10 runs, and the number of iterations is 2000 times. Compared with ACA, IQPSO has obvious shortcomings in three results except customer satisfaction; compared with GA, IQPSO has distinct advantages in three results except customer satisfaction. From this viewpoint, IQPSO is better than GA, but worse than ACA.

However, if cost and customer satisfaction in the table are the cost and customer satisfaction of all RVs, they can be converted into the cost and customer satisfaction of a single RV. The cost of a single RV calculated by IQPSO is 346.5625 yuan; the cost of a single RV obtained by GA is 307.1154 yuan; the cost of a single RV got from ACA is 432.4404 yuan. The customer satisfaction of a single RV obtained by IQPSO is 1.0512; the customer satisfaction of a single RV got from GA is 0.8287; the customer satisfaction of a single RV calculated by ACA is 1.8811. In terms of the cost of a single RV, compared with ACA, IQPSO saves 19.86%, and GA saves 28.98%. In terms of the customer satisfaction of a single RV, compared with GA, IQPSO increases 21.67%, and ACA increases 55.95%. According to the above analysis, if only considering the cost of a single RV, IQPSO is better than ACA, but worse than GA; if only considering the customer satisfaction of a single RV, IQPSO is better than GA, but worse than ACA. However, the mathematical model proposed in this paper are to balance relationship between the distribution costs and customer satisfaction. From this standpoint, IQPSO is the best of the three algorithms.

In order to further verify the effectiveness of IQPSO, this paper makes another experiment under snow conditions with different algorithms, as shown in Fig. 5. The distribution route shown in this figure is the best route in 10 operations for each algorithm. The optimal number of RVs obtained by IQPSO is 8, GA is 8 and ACA is 4. The optimal distribution route of IQPSO is: 0-13-0; 0-7-0; 0-6-11-16-0; 0-17-9-0; 0-2-4-12-10-0; 0-8-0; 0-15-14-0; 0-1-5-3-0. The optimal distribution route obtained by GA is: 0-11-0; 0-6-2-17-0; 0-4-0; 0-10-9-0; 0-3-0; 0-13-14-8-0; 0-16-12-5-7-0; 0-15-1-0. The optimal distribution route obtained by ACA is: 0-12-16-6-4-5-0; 0-7-9-14-15-17-0; 0-13-11-1-8-0; 0-3-2-10-0.

TABLE X
SIMULATION RESULTS FOR DIFFERENT ALGORITHM IN SNOW

Algorithms	Number of RV	Cost/yuan	Customer satisfaction	Driving distance/km
IQPSO	8	2808.71025	8.52023	130.2952
GA	10	3150.1584	9.12977	144.0742
ACA	4	1686.658986	7.63124	98.7036

TABLE X also compares four results (the number of RVs, distribution costs, customer satisfaction and driving distance of RVs) obtained by different algorithms under snow conditions. The comparison result is the average result obtained by different algorithms under 10 runs, and the number of iterations is 2000 times. Compared with ACA, IQPSO has distinct defects in three results except customer satisfaction; compared with GA, IQPSO has apparent advantages in three results except customer satisfaction. From this standpoint, IQPSO is better than GA, but worse than ACA.

However, if cost and customer satisfaction in the table are the cost and customer satisfaction of all RVs, they can be converted into the cost and customer satisfaction of a single RV. The cost of a single RV calculated by IQPSO is 351.0888 yuan; the cost of a single RV obtained by GA is 315.0158 yuan; the cost of a single RV got from ACA is 421.6647 yuan. The customer satisfaction of a single RV obtained by IQPSO is 1.06503; the customer satisfaction of a single RV got from GA is 0.91298; the customer satisfaction of a single RV calculated by ACA is 1.90781. In terms of the cost of a single RV, compared with ACA, IQPSO saves 16.74%, and GA saves 25.29%. In terms of the customer satisfaction of a single RV, compared with GA, IQPSO increases 14.28%, and ACA increases 52.15%. Based on the above analysis, if only considering the cost of a single RV, IQPSO is better than ACA, but worse than GA; if only considering the customer satisfaction of a single RV, IQPSO is better than GA, but worse than ACA. However, the mathematical model proposed in this paper are to balance relationship between the distribution costs and customer satisfaction. From this viewpoint, IQPSO is the best of the three algorithms.

VII. CONCLUSION

In the era of the construction of smart cities, intelligent distribution will become an important part of people's daily life, especially the FAP's distribution with higher requirements. This paper aims to study the FAP's intelligent distribution in smart cities. In order to formulate distribution routes scientifically and reasonably, which balances the relationship between distribution costs and customer satisfaction, we establish a mathematical model. By using IQPSO for related experiments, the effectiveness and stability of the algorithm are verified. The results show that the established model and the algorithm used can effectively balance the relationship between distribution costs and customer satisfaction. Therefore, it provides a new solution for balance the relationship between distribution costs and customer satisfaction in FAP's intelligent distribution in smart cities. In our future works, we will study the mathematical model of VRP with multi supply points and multi demand points. In addition, we will arrange different types of vehicles to provide distribution services for customers with different demands.

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